Wavelet-Based Fault-Tolerant Integration and Target Recognition in Multidimensional Sensor Signal Processing

Progress Report

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Dr. S.S. Iyengar
Dr. B.J. Jones

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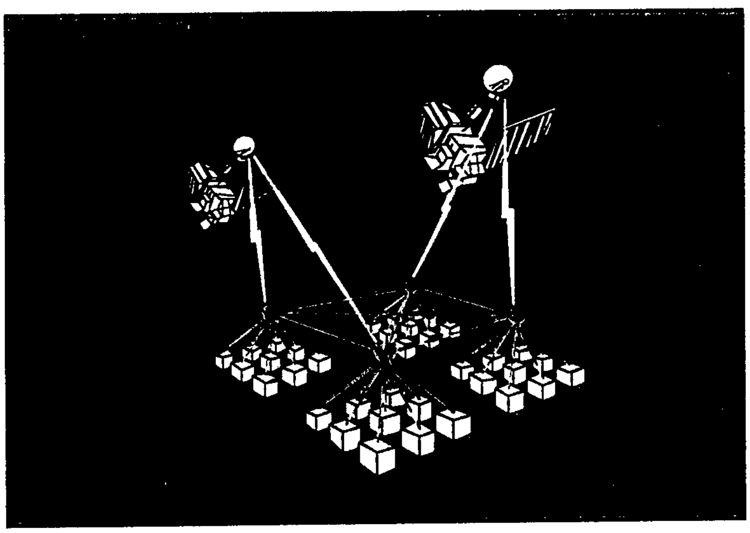

Louisiana State University
Department of Computer Science
Baton Rouge, Louisiana 70803-4020
http://trap.rrl.lsu.edu

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Executive Summary

Sensor fusion research has been motivated by the difficulty of implementing automated systems which interface with the real word. For a system to react properly to a changing environment, the system requires sensor input to model its environment. Unfortunately, sensors are electromechnical devices in most cases and subject to physical limitations. There physical limitations manifest themselves as constraints on the accuracy, precision, and dependability of the data returned by the sensors. It is computationally challenging for an autonmous system to robustly evaluate sensor data of questionable accuracy and dependability. Sensor fusion seeks to solve this problem by taking inputs from several physical sensors and merging the individual physical sensor readings into a logical sensor reading. This has several advantages, some of which are particularly salient to this research effort. The use of heterogenous physical sensor allows a logical sensor to be developed which is less sensitive to the limitations of any single sensor technology.

Major significant results were attained in the following key areas of sensor fusion research:

- A new computational framework for detection-localization sensor systems which is a multidimensional approach to Kadota's Method
- New techniques for registration of correlated noisy and uncorrelated images containing periodic and nonperiodic components
- A unique wavelet-based image compression technique
- A novel mathematical model of image registration
- Fault tolerance in a multisensor environment
- Develop an algorithm for efficiently computing the availablity of a fault masking system given component reliability statistics
- Find the minimal cost sensor configuration which fulfills the given system dependability requirements

As a result of our research endeavors, we have contributed significant articles to the research community during the period 1995-96. In particular, we have published

- 2 books (with another under review);
- 14 peer reviewed journal papers;
- 5 conference proceedings articles.

This research effort has also produced two Ph.D. students. Dr. Iyengar has received several commendations during the past, among them the LSU Distinguishing Faculty Award for Research Excellence and the Tiger Athletic Foundation Award, as well as several invited talks.

Sensor fusion research is a continuous process of discovery which produces results that can be applied in real-world applications. The following pages highlight the results of the sensor fusion research during the past year.

Research Accomplishments

Detection-Localization Integration in Sensor Systems: A Multidimensional Approach to Kadota's Method

Introduction

Sensors technology is playing a more invasive role in automated systems in unpredictable environments. Examples of such systems include aerospace radar systems, satellite surveillance and mapping, robotic binocular vision, and integrated virtual reality systems. In these and other applications, the combination of a suite of sensors to measure some environmental phenomenon ensures that a system receives a realistic view of its environment.

The combination of sensor readings into a meaningful result, or sensor integration (fusion), may be of different types. *Competitive sensor integration* is an integrated sensor system where each sensor in the system returns essentially the same information. The difference in readings results from sensor failure or random noise. An example of this type of system is a process control system with an array of identical sensors measuring temperature of a physical process. The other type of sensor integration strategy is *complementary sensor integration.* Information from sensors which measure partial on different information is fused to provide a conherent reading of the physical entity under interest. A binocular vision system for a robot is an instance of this type of integration, each camera measuring partial images to be correlated and used for recognition.

Kadota [1] has proposed a sensor integration problem with two sensors with disparate capabilites and limitations. His *detection-localization system* involving integration of two non-identical sensors is modeled after two satellite surveillance devices. The first sensor models EM radiation in the visible light spectrum and is affected by both non-Gaussian random noise (clouds) and Gaussian noise. The second sensor measures EM radiation in the infrared region and is affected by Gaussian noise only, but its resolution capabilites are less than that of the first sensor. Figure 1 is an abstract representation of such a system.

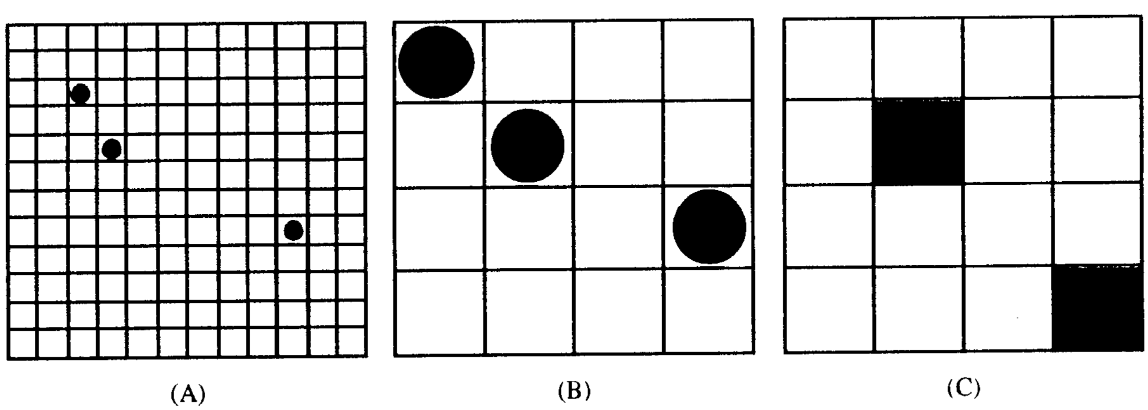

Figure 1: (A) represents a high resolution sensor readings. The blue circles indicate target positions. (B) represents a low resolution sensor reading covering the same area as sensor 1. The red circles represent the same targets at a much coarser resolution. (C) represents cloud positions relative to the two sensor readings.

Kadota formulates the problem in a series of four equations which model the two sensors in the presence and absence of a target ([1]). His model and solution have the following limitations:

- Only one target is considered possible in the area under consideration;
- The number of clouds in the area of examination is assumed to be known beforehand, which is an unrealistic assumption;
- Cloud removal involves computation of a combinatorial function and, hence, is not suited for large problems if results are needed in real-time.

Technical Approach

We have proposed a new framework to solve the problem of complementary sensor integration posed by Kadota. Our approach makes the following assumptions, which are fewer than in ([1]):

- Multiple targets are allowable;
- No assumptions are made about cloud number, position, size, shape, or density other than clouds are typically assumed to be larger than targets;
- Cloud removal detection, cloud removal, and white noise removal algorithms can be polynomial in time (for real-time operation).

Our formulation of the problem is similar to that proposed by Kadota, but is given here in a form more convenient for describing the our Kalman filter approach.

$$z_1(t) = H_1(t,v) * x(t) + g_1(t) + v(t)$$
$$z_2(t) = H_2(t) * x(t) + g_2(t)$$

where, at time t,

$z^1(t)$ = the noisy reading of sensor 1 from its $n \times n$ grid, represented as an n^2 vector

$z^2(t)$ = the noisy reading of sensor 1 from its $m \times m$ grid, represented as an m^2 vector

$x(t)$ = the system state from its $n \times n$ grid, represented as an n^2 vector

$g_1(t) \approx N(0,r_1)$ = Gaussian noise in sensor 1, as an n^2 vector

$g_2(t) \approx N(0,r_2)$ = Gaussian noise in sensor 2, as an m^2 vector

$v(t) \approx P(\lambda)$ = non-Gaussian (cloud) noise in sensor 1 as an n^2 vector

$H_1(t,v)$ = Time varying measurement matrix ($n^2 \times n^2$) for sensor 1

$H_2(t,v)$ = Time varying measurement matrix ($m^2 \times m^2$) for sensor 2

We have followed a layered approach to to filter out the two different types of noise before integrating the sensor readings. This approach has the advantage of being computationally efficient and robust, and allows for the use of established techniques for filtering Gaussian noise, such as the Kalman filter. Specifically, our strategy uses a cloud detector to detect portions of the first sensor reading affected by the non-Gaussian noise described by Kadota. This type of noise not only is additive but also causes attenuation of the signal of interest. A cloud removing filter then attempts to eliminate the non-Gaussian noise from that reading. The standard approach of using an extended Kalman filter is then used to filter

the Gaussian nosie present in both sensor readings. Figure 2 illustrates our layered approach.

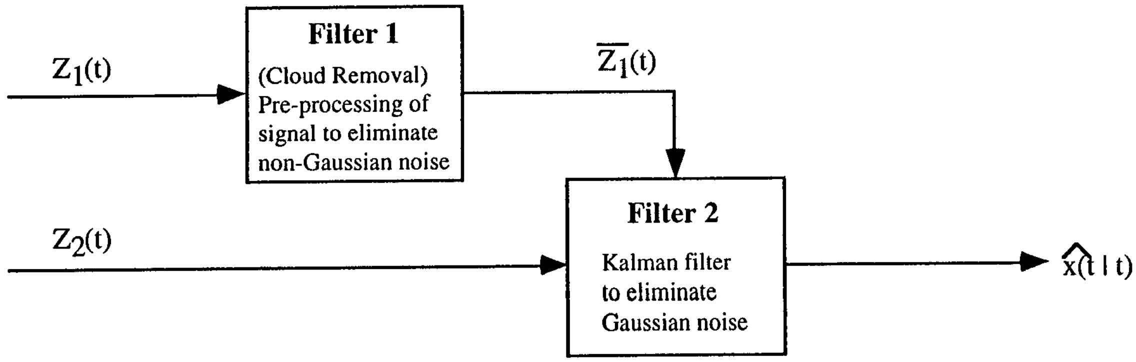

Figure 2. Layered Approach to Noise Filtering

The details of the cloud detection, cloud removal, and Gaussian noise removal algorithms and corresponding mathematical formulation are presented in [2]. The target prediction scheme is presented there also.

Major Results

We have developed a sophisticated simulation to verify our model and algorithms. The structure of the simulator is given in Figure 3. The top portion simulates the environment by creating noisy sensor readings from the input position of the target and clouds. A Gaussian random number generator is used to generate the white noise. The bottom portion simulates the cloud detection and removal, white noise removal, target prediction, and display. There is a sharp delineation between the two in the sense that the target prediction component has no knowledge of the environment simulator apart from the noisy sensor readings given by the latter.

We have simulated three different scenarios:

- Multiple targets present; no clouds (thus, no cloud removal); white noise filter employed.
- Multiple targets present; some targets are occluded by clouds, but no cloud removal algorithm is employed; white noise filter employed.
- Multiple targets present; some targets are occluded by clouds; cloud removal algorithm is employed; white noise filter employed.

The graphical plot shows the results of our simulations for the second scenario. The horizontal axis in each plot represents the position of elements in the grid. The vertical axis represents signal strength. The relevant plots to consider are the plot of the actual location of the target and the plot of node number (generally, the first and last plots on each page). As seen in this plot, our algorithms detected each of the actual targets using our advanced cloud detection and filtering algorithms. Results for the first and third scenarios are similar.

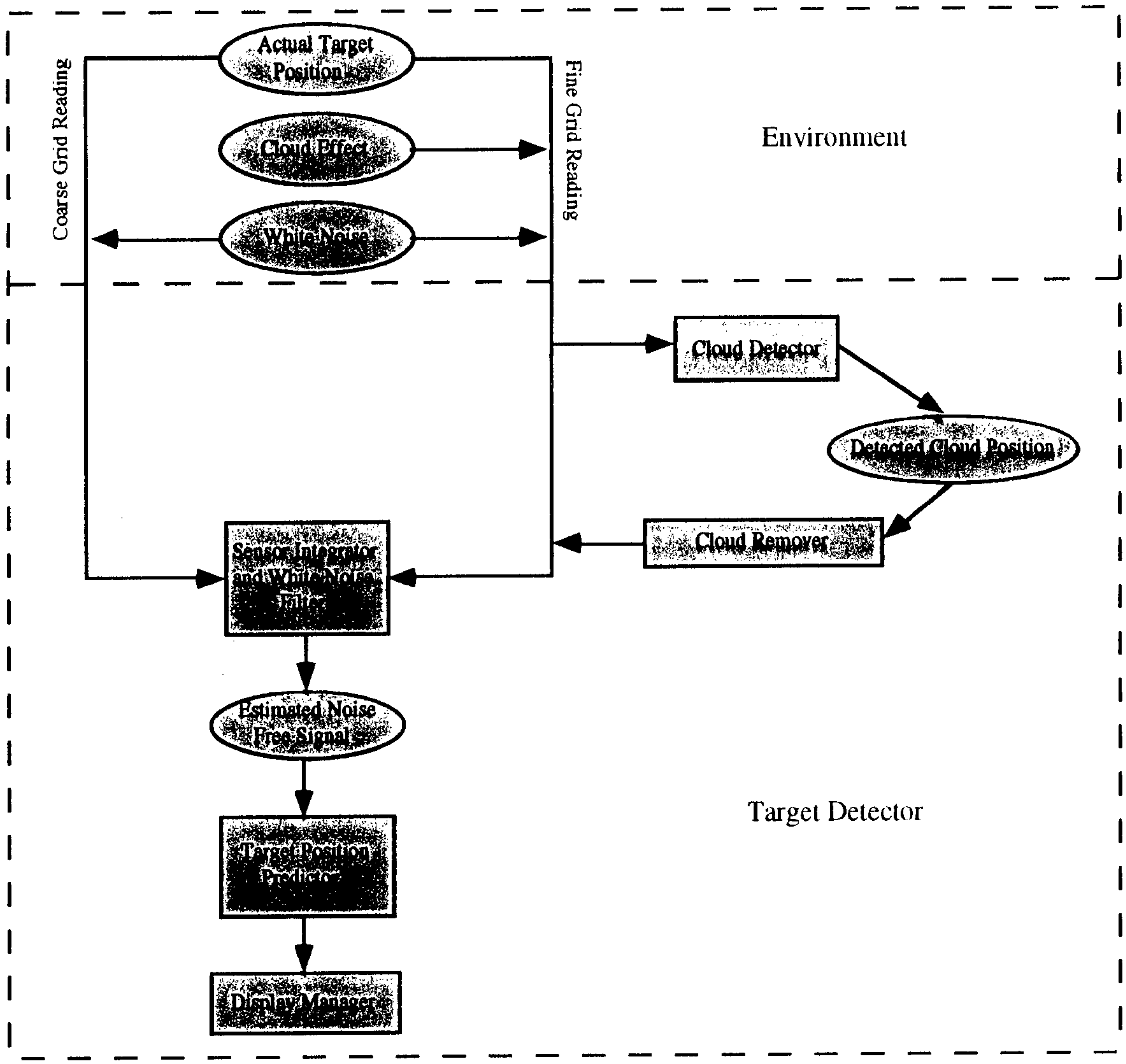

Figure 3. Simulator Stucture

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A Genetic Algorithm Approach to Image/Sensor Correlation and Calibration

Introduction

The ultimate goal in sensor research is to produce systems which interact in a real-world environment. This environment has the characteristic of being undefineable, and the sensors with which robots must perceive are inherently noisy and have limited accuracy.

Machine learning algorithms use specific instances of data to build general concepts and internal models for use by the robot. Traditional machine learning algorithms are generally intolerant of noisy and inaccurate date. However, genetic and connectionist paradigms are usually more tolerant of noise in the data source

This research effort investigates a signal processing application of genetic algorithms involving the interpretation of noisy and inaccurate sensor data. Specifically, the problem is to establish a correlation between grayscale images from two separate sensor sources (Figure 4). Our approach to this problem is unique and general, and the solution is applicable to many real-world problems. In particular, our approach is well-adapted to the area of *active vision*, a recent approach to computer vision emphasizing active, i.e. dynamic, participation in the real world.

Formally, the problem statement is

Given noisy grayscale data readings from sensors one and two, find the optimal set of parameters {x-displacement, y-displacement, angle of rotation} which defines the center of the sensor two image relative to the center of the sensor one image.

The optimality of these parameters is established as the best mapping of sensor two's readings to the readings of sensor one.

We assume that two sensors return two dimensional gray scale data from the same environment. The sensors have identical geometric characteristics and return circular images. It is known that the two sensor readings overlap and contain noise, but the relative positions of the two sensors are not known. As stated above, the reading from sensor two is translated and rotated with respect to the reading from sensor one. Also, the two readings may have differing levels of noise present. In Figure

The following equation describes the model used to describe the terrain.

$$\begin{aligned}\text{terrain}(x,y) = 100.0 + (&-40 * x + 45 * y - 0.003 * x * y + 0.02 * x^2 - 0.01 * y^2 \\ &-20 * y * \sin(x/18) + 35 * y * \cos(y/29) - 35 * \sin(x/4 - y/12) \\ &+12 * x * \cos(x * y/100))/100\end{aligned}$$

This equation has certain characteristics which make the problem not trivially solvable, namely that it contains both periodic and non periodic elements. The non-periodic elements ensures that a unique best match for the two sensors exists. The periodic elements ensure that the match is not trivially found, i.e., the search strategy will have to deal with local minima in the search space, a phenomena aggravated by the presence of noise in the sensor readings.

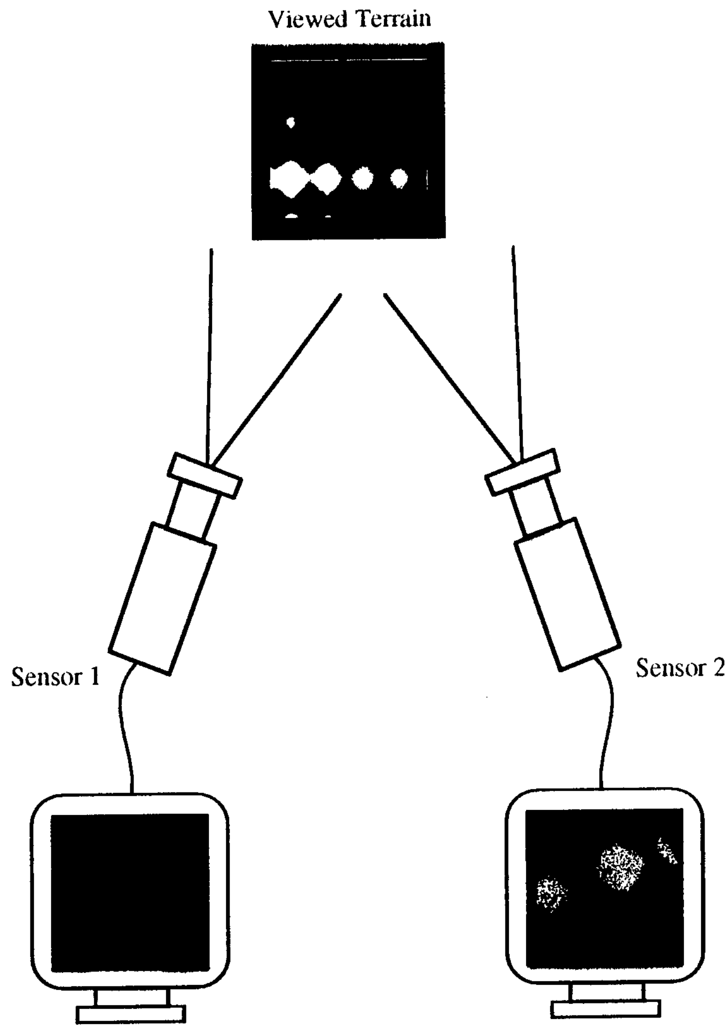

Figure 4. Terrain and Sensor Configuration

Technical Approach

Three different approaches were used to establish image correlation between the two sensor readings with the same fitness function being used by all three. Also, all three algorithms are studied with data corrupted by Gaussian noise.

The first search approach is called "taboo search". It involves searching with a modified heuristic from accounting of most recently visited nodes in the search space. Points in this list are then labeled "taboo" and are not visited again while present in the list. One drawback of this approach is that a clear stopping criteria is almost impossible to define. However, the algorithm requires less computation than other approached, such as simulated annealing.

The second and third approaches are genetic algorithms by nature. They differ in the strategy used for reproduction. The first genetic algorithm used is the classic approach described by Holland [2].

The second approach uses elite genetic algorithms. The algorithm is described as elitist since 20% of the strings with the best fitness function values are propagated into the next generation gene pool. In addition, our implementation uses random mutations for 3% of the

strings in the next generation. The remainder of the new generation is formed using random crossover of strings in the current generation.

Major Results

The same sensor readings were applied to each of the three algorithms although each iteration of each algorithm was performed with new sensor readings. After each iteration, a new noise value was introduced into the sensor readings by increasing the variance of the Gaussian noise, thus simulating dynamic readings in time. The same geometric region was used for each of the sensors.

The elitist genetic algorithm approach yielded the best results of the three algorithms. The taboo search method, while taking a consistent path in varying noise situations, tended to move towards locally optimal values, which were not close to the globally optimal. The reason for this is that the taboo search mechanism only considers points in the search space in the immediate vicinity. The classical genetic algorithm approach exhibited convergence to non-global optimal values. The elitist genetic algorithm approach tended to converge to globally optimal values of the fitness function in sensor readings with low to moderate noise and it did so rapidly.

The problem we set out to solve was to find ways of automatically calibrating two noisy sensors using optimization techniques. We have shown that this approach is possible in situations where the noise in the sensor readings is within certain bounds.

Future Directions

Future directions of this work include the investigating the effect of changing the image as well as the noise in each iteration of the three algorithms. Since local minima would then become a transient phenomena, the problem might be easier to solve. This exploration would be especially relevant to sensor arachitectures for real-time systems research.

Other future directions include hybrid genetic algorithms with a greedy heuristic, using a multiresolution approach by matching every *n*th pixel, and considering scaling along with translation and rotation for matching goals.

Pertinent Publications

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Configuration Cost Minimization in Fault Masking Multisensor Systems

Introduction

Multisensor computing systems are made up of a large number of individual components. If these systems are to operate correctly for any length of time, care must be taken to design them so they can tolerate failures of individual components. High reliability systems often use redundant modules to mask errors and tolerate failures in a fixed percentage of the redundant modules.

Given choices among the different types of modules which fulfill the system's requirements but have different reliability parameters and per item cost, it is possible to find the number of redundant modules needed to meet the system reliability requirements. Our work presents new techniques for finding the combination of modules which fulfills system reliability constraints and has the lowest cost. Our methods search a subspace of the problem space which must contain the optimal solution. If the number of modules to be considered is large, the computational complexity of an exhaustive search may be prohibitively expensive. Two heuristic methods using simulated annealing and genetic algorithms, respectively, have also been developed

Techniques

To determine a dependability analysis for a set of components, we construct a geometric surface that divides the region made up of points which satisfy the reliability requirements for the rest of the n-dimensional space. By separating the points which satisfy the dependability requirements from those which do not, this surface effectively defines a half-space of acceptable answers.

> **Lemma**. The optimal answer must lie on the surface dividing the n-dimensional problem space into two regions: one region containing points which satisfy the dependability requirements and one region containing point which do not satisfy the dependability requirements.

Since the lemma ensures that the optimal answer must lie on the surface, it is necessary to consider the surface's exact shape. The shape of the surface is given by equations (1) and (2).

$$R(t) = \sum_{p=0}^{k}\left[\binom{k}{p} r_1(t)^p (1 - r_1(t))^{k-p} \sum_{q=\lfloor N/2 \rfloor+1-p}^{m}\left[\binom{m}{q} r_2(t)^q (1 - r_2(t))^{m-q}\right]\right] \qquad (1)$$

$$a_{sys} = \sum_{p=0}^{k}\left[\binom{k}{p} a_1{}^p (1 - a_1)^{k-p} \sum_{q=\lfloor N/2 \rfloor+1-p}^{m}\left[\binom{m}{q} a_2{}^q (1 - a_2)^{m-q}\right]\right] \qquad (2)$$

Equation (1) measures the system reliabilty given two components, and equation (2) measures the system availability. No assumptions are made regarding the shape of the surface.

An exhaustive search algorithm was developed since it is guaranteed to find the minimal cost solution by considering all points on the surface. However, since the computational complexity of this search method is exponential in the number of types of components

under consideration, it is unsuitable for use given a large number of component types. Thus, it is necessary to consider other search methods that are able to provide solutions to the optimization problem.

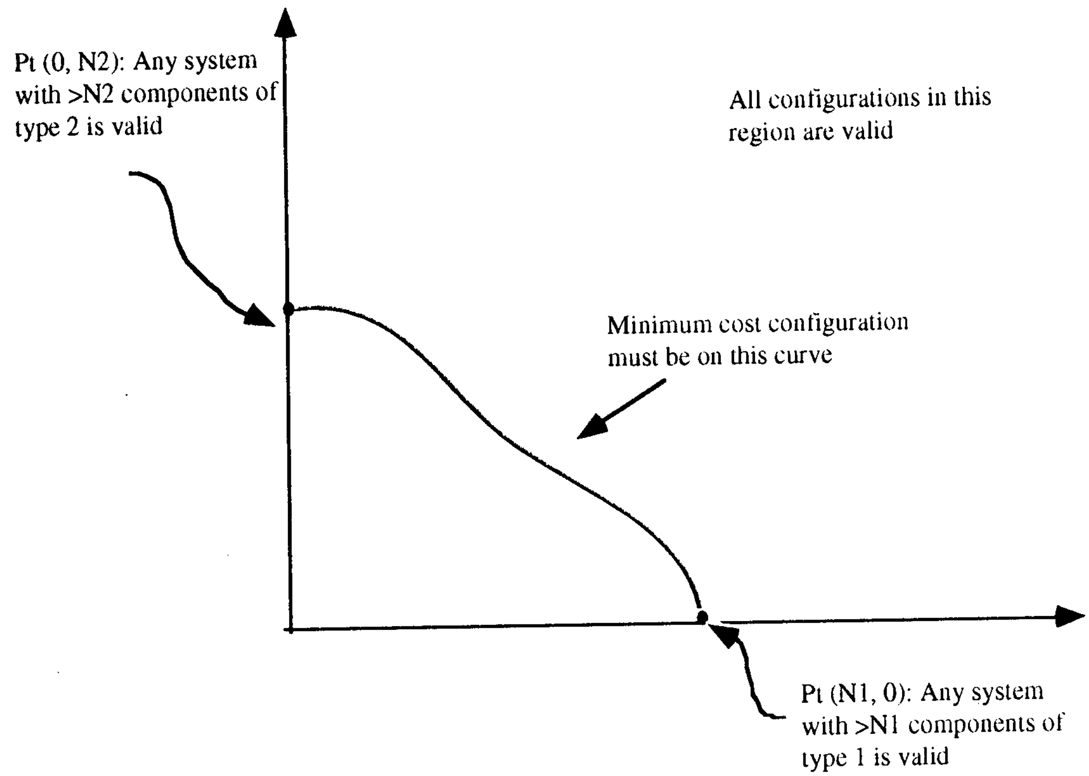

Figure 5: Valid half space of configuration surface

It is important to use heuristic search methods which are not sensitive to local minima in the surface. Methods such as simulated annealing and genetic algorithms are able to find good, if not optimal, combinations of components in less than exponential time. We have verified this by applying these methods to this problem.

We have used an elitist genetic algorithm to solve this optimization problem (previous article). The solution space to the optimization problem consists of configurations of components for which the chromosomes used by the GA consist of a vector which describes a possible system configuration. The fitness function used in determining the relative quality of chromosomes is the cost of the configuration described by the chromosomes. The elitist reproduction strategy employed uses the following approach

- copies the best 20% of the current gene pool intact into the next generation gene pool
- determines 75% of the next generation gene pool by randomly mixing elements from two chromosomes chosen at random from the current generation gene pool
- randomly mutates 5% of the next generation gene pool

This approach is taken since it is shown that the quality of the best answers will increase monotonically.

In our simulated annealing approach, the basic strategy of the algorithm is based on using a fitness function to compare relative merits of various points in the problem space. The problem space is described by vectors which correspond to possible configurations and the

fitness function if the cost of the configuration described by the vector. The cooling schedule used n this application starts with a temperature of 1.0 which decreases at a rate of 10%. The total number of iterations at a given temperature was limited to 100*j and the maximum number of positions visited at a given temperature was limited to 10*j.

Major Results

Results from sample problems indicative of real world sensor systems show a 4% to 10% cost savings where combinations are found compared to the least expensive system consisting of only one component type. The test cases used in our experiments consists of eight and eleven dimensions. The number of dimensions was kept low to allow the evaulation of the exhaustive search for determination of the global minimum.

In out test cases, simulated annealing always found the global minimum and was the least computationally intensive of the three approaches. However, while encouraging, we note that the simulated annealing approach is not guaranteed to find the global minimum.

The elitist genetic algorithm found either the global minimum or an answer within 1% of the global minimum. This algorithm is more computationally intensive than simulated annealing and has no definite stopping criteria. However, the genetic algorithm is computationally better than the exhaustive search method, and its best answers are guaranteed to be monotonically decreasing.

We conclude that in small cases, the exhaustive search is the best search method to use since it absolutely guarnatees a globally optimal minimal cost. However, in cases where the number of component types is large, the simulated annealing approach appears to be the best methodology to use in solving this problem. A reasonable approach would be to use the elitist genetic algorithm as a secondary step to verify the results produced by the simulated annealing algorithm.

4. K-Systems Theory

The problems of distributed sensor networks were couched in the 1992 systems paper into the framework of K-Systems theory. As well, K-Systems theory can be used across a spectrum of problems of interest to the ONR. In general, K-Systems theory can be used on any problem that involves data analysis. Basic research into K-Systems theory became the focus of our attention.

A new algorithm for isolating roots of nonlinear equations was developed as a by-product. This algorithm is of value on any nonlinear system in applied mathematics. K-Systems research also led to a means of accelerating the convergence of slowly convergent algorithms in applied mathematics. Further, the computation of interactions in K-Systems theory was defined. Interactions in statistics depend on a linear model. A new concept of interaction that depends on entropy mathematics was developed.

Parallel K-Systems algorithms were designed and implemented, and the algorithms were extended to probabilistic systems. Finally, explanations have been given for the startling accuracy of K-Systems analysis.

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